Real-time Ground Estimation and Point Cloud Segmentation

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Outline

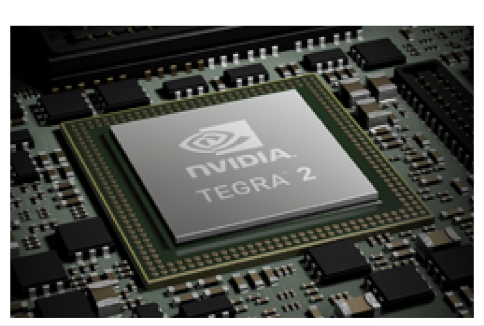
- A **generic ground form model**.
- Its **efficient estimation method**.
- Fully-integrated **ground-related point cloud segmentation**.
- **Parallelized process** on **GPU**.
- **Real-time** performances on **embedded devices (TX2)**.
- Applications to **ADAS** and **Autonomous Driving** frameworks
- **Validation** in **simulation** and **real experiments**

Context

- Development of low cost sensors and miniaturized computing units will enable advanced perception technologies to be embedded on realistic products.
- Many sensors provide 3D point clouds representing the geometry of the scene.
- Most perception solutions (object detection, occupancy grid generation, etc.) require a distinction between ground-related and obstacle-related points.
- This distinction necessitates a ground form estimation, complex enough to represent non-planar grounds, but efficient enough to provide real-time performances under the resource constraints of embedded devices.

Experimental Platform

- **Virtual platform** under **Gazebo**, with **realistic simulation** of motion, odometry and lidars.
- **Experimental platform on Renault Zoe**, equipped with Velodyne HDL64E, 4 Ibeo Lux LiDARs. Interconnection of sensors and programs using **ROS** middleware.
- Computations run on **Jetson Tegra X2**.



Ground Model

- **Spatio-Temporal Conditional Random Field**, sequence of regular planar nets of nodes N_i, to each node is associated a variable $G_i(h_i, sx_i, sy_i)^T$ representing the elevation and two directional slopes of the ground.
- Each data point (x_j, y_j, z_j) is associated to the closest node, C_j representing its belonging to the ground.
- Each G_i is related to potential functions.
  - **Measurement potential**:

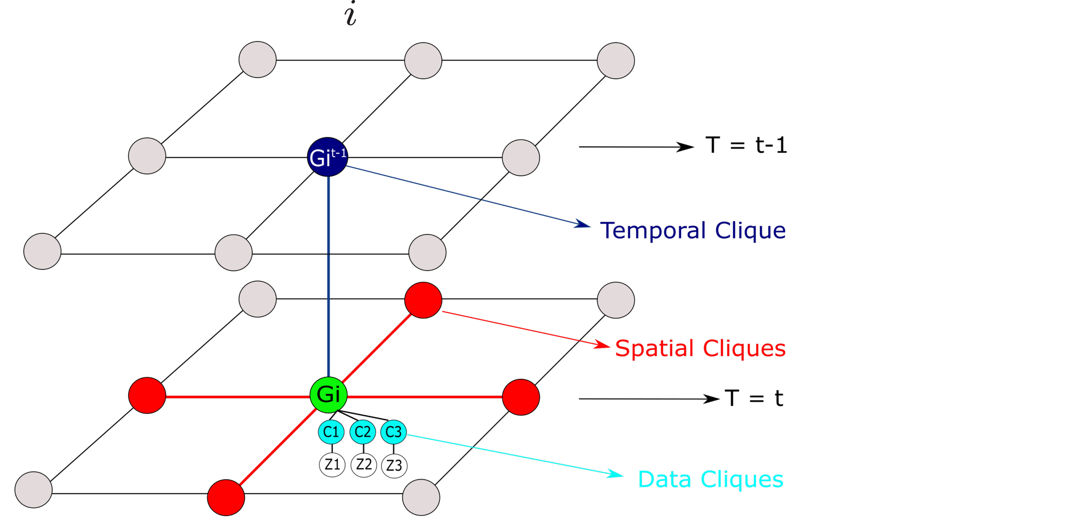
$$\psi \equiv exp(-\sum_i \alpha \sum_{j \in \mathcal{M}_i} c_j ||z_j - H_{ij} G_j||^2) \quad (1)$$

  - **Spatial potential**:

$$\Phi \equiv exp(-\sum_i \beta \sum_{j \in \mathcal{N}_i} ||G_i - F_{ij} G_j||^2) \quad (2)$$

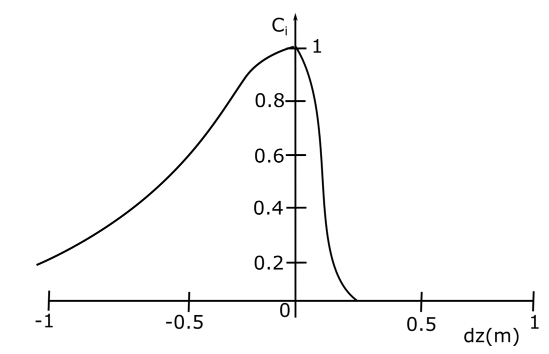
  - **Temporal potential**:

$$\xi \equiv exp(-\sum_i \gamma ||G_i - Q_i G_i^{t-1}||^2) \quad (3)$$



Model Inference

- G_i approximated to **Gaussian distributions**, leading to linear computations using information vectors and matrices (inverse of specified elements).
- **Expectation-Maximization**-like method, in parallel for every node.
  - **E step** : compute for each data point $P(C_i)$ to belong to the ground, depending on its height dz relative to the predicted ground elevation G_i



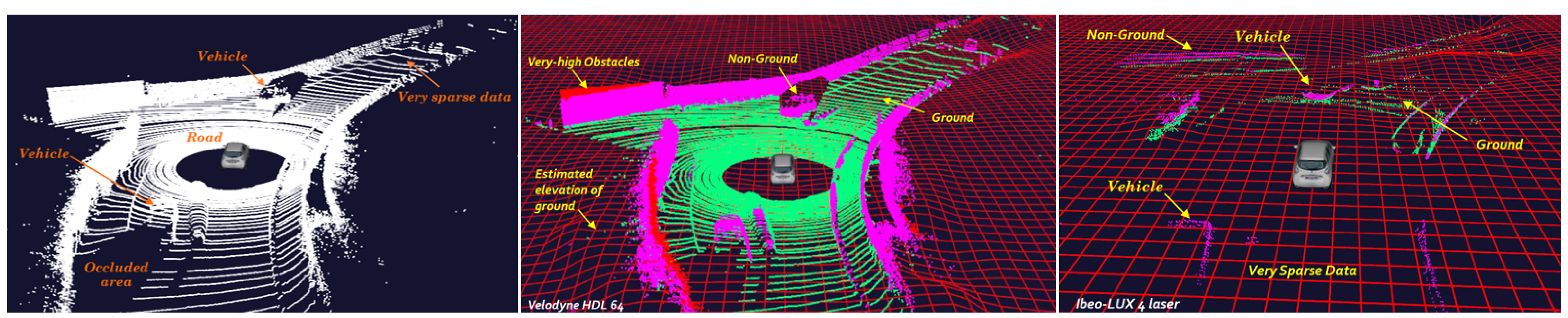
  - **M step** : compute G_i which minimizes the sum of the 3 potential functions (eq 1,2,3)

$$X_i^{k+1} = \alpha \sum_{j \in \mathcal{M}_i} c_j z_j H_{ij}^T + \beta \sum_{j \in \mathcal{N}_i} F_{ij}^T X_j^k + \gamma Q_i^T X_i^{t-1}$$

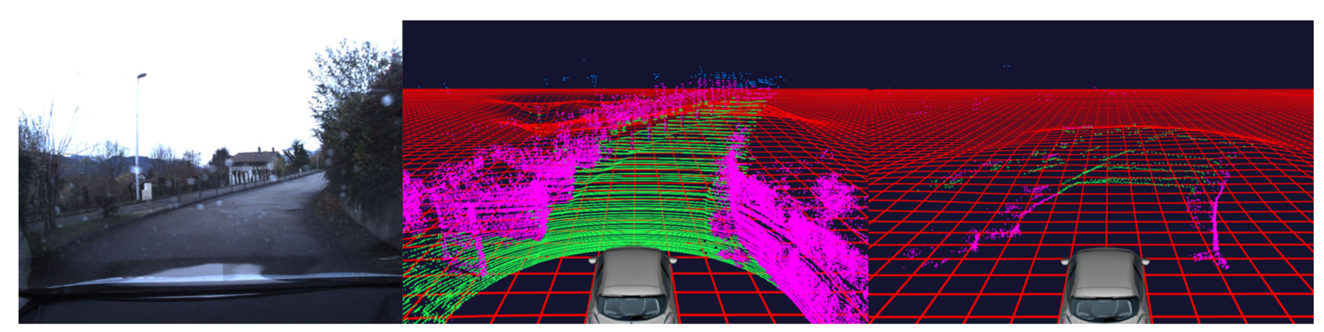
$$P_i^{k+1} = \alpha \sum_{j \in \mathcal{M}_i} c_j H_{ij}^T H_{ij} + \beta \sum_{j \in \mathcal{N}_i} F_{ij}^T P_j^k F_{ij} + \gamma Q_i^T P_i^{t-1} Q_i$$

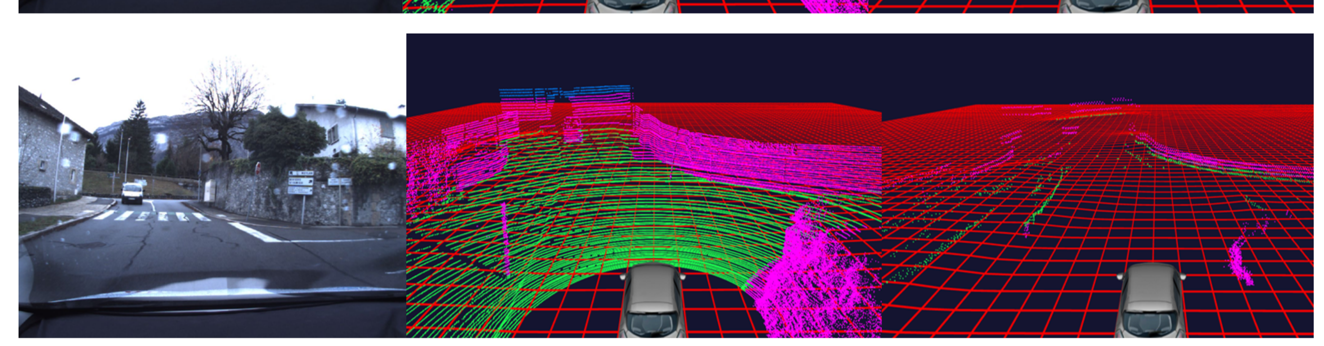
- Parallelized processing on GPU at every step, over sensor point cloud data in E steps, over ground elevation nodes in M steps. **Fully-integrated** in a global **GPU-based perception framework** (detailed in Applications)

Results



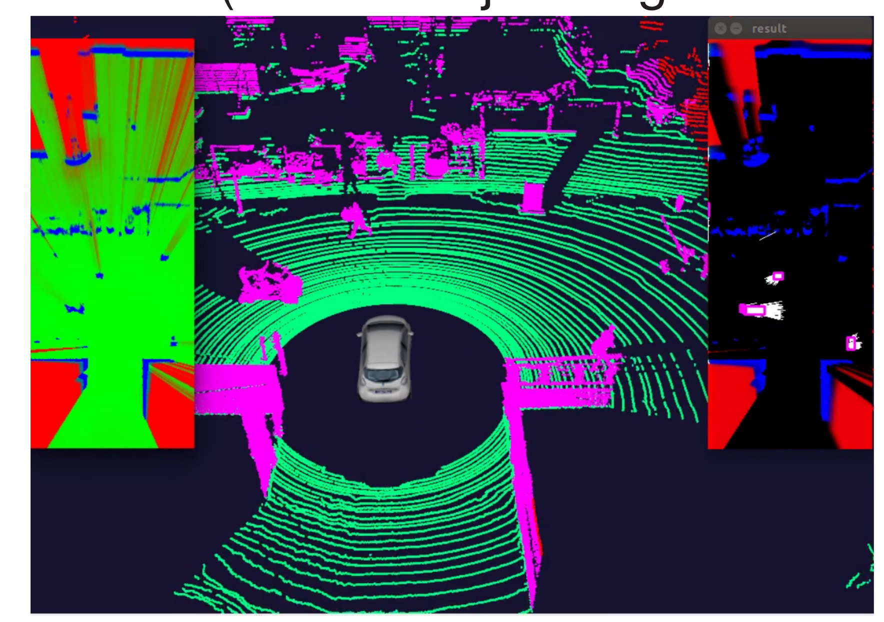
- Perception tested on **real road data** in various experimental environments (inner city, countryside, highways, mountain roads, etc.)
- **No prior knowledge** of the road
- With Velodyne or fused Ibeo point-cloud inputs
- **Real-time** ground estimation and data classification on **TX2**





Applications

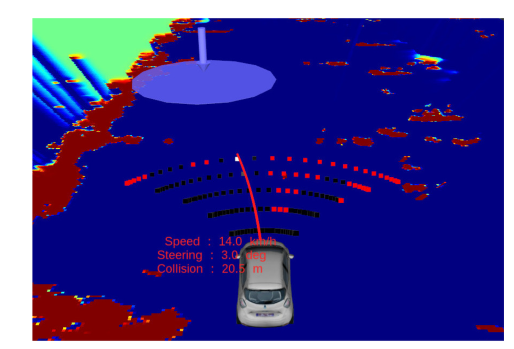
- Generation of **occupancy grids**, consistent with the classified point cloud and estimated ground model.
- Occupancy grid **filtering and tracking** over time, combined with **velocity inference**, at cell level (without object segmentation)



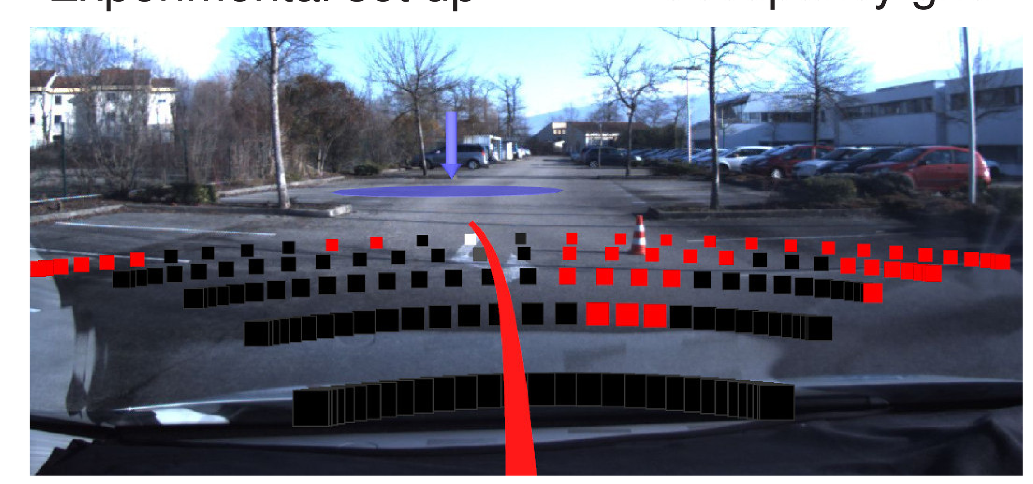
left : generated occupancy grid
right : filtered grid, with inferred velocity vectors

- **Grid-based collision risk** and time-to-collision estimation
- **Automatic emergency braking**, according to these potential collision estimates.
- **Autonomous driving**, by local pathfinding, using a **Dynamic Window Approach** (selection of the best trajectory in a set of online-computed trajectories).
- Validation in **simulation**, and **real experiments** with experimental platforms on a dedicated infrastructure, replicating realistic urban scenarios.

Experimental set up



Occupancy grid



Dynamic window and path leading to goal

Acknowledgements

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